PERSISTENCE OF GEOPOLITICAL RISKS IN DEVELOPED AND DEVELOPING COUNTRIES

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ABSTRACT

This paper examines geopolitical risk in terms of time series persistence. In doing so we are able to determine the nature of the shocks, which are either transitory or permanent depending on the integration order of the series. We examine 19 countries from January 1985 to February 2020. Our results show evidence of positive time trends in the cases of Mexico and Venezuela, and negative ones for South Africa and Argentina. These results are robust across seasonal and non-seasonal data and for different modelling assumptions for the error term. With respect to the degree of persistence, the different parameter is found to be in the range (0, 1) although we also observe heterogeneity across all countries.

Keywords: Geopolitical risk; persistence; fractional integration

JEL Classification: C22; F42; F50

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1. Introduction

Geopolitical risk is the risk arising from tensions (including nuclear tensions) between countries, wars and terrorist incidents that affect the regular and pacific course of global relations. Geopolitical risk inculcates both the risk that these events generate as well as the additional risks resulting from the escalation of prevailing events (Caldara and Iacoviello, 2018). Geopolitical risk could include, for example, a flare-up of tensions between two major oil producing countries that resulted in a spike in the price of oil. Battle for supremacy among the world superpowers, continuous conflicts in the Middle East and beyond are also examples of current events that generate geopolitical risks. Incidents that are not frequent but also referred to as being geopolitical include climate change, major democratic political episodes such as Brexit, and global economic incidents such as the global financial crisis of 2007-2009 (Caldara and Iacoviello, 2018).

Most geopolitical events are likely to affect several countries because these events are global in nature and also for the fact that the world is increasingly becoming more interconnected. The importance of geopolitical risks is numerous. Geopolitical risks alongside economic and policy uncertainty are regarded as the `uncertainty trinity' that could have sizable negative economic consequences (Carney, 2016). Due to the concerns about the economic effects of the various diplomatic and military conflicts taking place around the world, geopolitical risk is regarded as more important than economic and political uncertainty (Caldara and Iacoviello, 2018). High levels of geopolitical uncertainty can force consumers to defer their consumption and cause companies to delay investment spending (Bloom 2009).

The existing studies on geopolitical risks have focused mainly on the economic impacts that countries face as a result of heightened geopolitical risks. For instance, Antonakakis et al. (2017) noted that geopolitical risks triggered negative effects on both oil returns and volatility. Aysan et al. (2019) showed that the geopolitical risks have predictive power on returns and price volatility of Bitcoin; and further revealed that negative changes in geopolitical risks significantly lead to greater Bitcoin returns. Caldara and Iacoviello (2018) revealed that geopolitical risk has adverse negative effects on real activity in the United States, including investment and stock returns. Demir et al. (2019) showed that geopolitical risks have negative effects on inbound tourism. Mansour-Ichrakieh and Zeaiter (2019) suggested that geopolitical risk in a country can trigger higher financial stability and financial vulnerability in other countries. Gupta et al. (2019) revealed that geopolitical risks have adverse effects on trade flows.

One of the aspects of geopolitical risks that is yet to be explored is the persistence of the series. Persistence captures the degree to which short term shocks in the current period will trigger long term future changes. A shock is said to have a temporary or short-term effect if, after a short period of time, the variables moves back to its original position or the effect of the shock quickly evaporates (Solarin et al., 2020). The magnitude of the persistence of geopolitical risks will determine the durability of the adverse effect of geopolitical risks on the financial markets as well as on the real markets. Hence, the magnitude of the persistence of geopolitical risks will also define the level of the remedial actions needed by policymakers to ameliorate the adverse impacts of the uncertainty shock. Besides, ignoring the unit root profiles of a variable under investigation or an incorrect examination of these properties can lead to unreliable empirical findings. In other words, conventional methods such as standard ordinary least squares (OLS) that are premised on stationary data could generate spurious estimates, when geopolitical risks have a stochastic trend. The fact that a geopolitical risk series is persistent indicates that it will be hard to accurately predict future values of the geopolitical risk series by merely relying on their past figures of geopolitical risks. Therefore, it will be difficult to predict macroeconomic variables and financial markets using information from the uncertainty variable (being a leading indicator).

Our paper provides two main contributions to the literature on geopolitical risks. First, we examine the persistence of geopolitical risks in 19 countries. Hence, the results of this study will provide hindsight regarding the duration of the shock results from geopolitical risks on the economy. Secondly, we use a fractional integration approach; a methodology that has not been used to measure persistence in geopolitical risk. This approach is more general than the standard methods that use AutoRegressions (AR), unit roots or other approaches based on integer degrees of differentiation.

2. Methodology

Fractional integration means that a series needs to be fractionally differenced to obtain I(0) or a short memory pattern. In other words, if d is a fractional value, x_t is said to be I(d) or integrated of order d if the d-differenced process, i.e., $(1 – B)^d$ x_t is I(0).[1] The fractional differencing polynomial $(1 – B)^d$ can be expanded in terms of its Binomial expansion, such that for all real d,

$$(1 - B)^d = \sum_{j=0}^{\infty} \binom{d}{j} (-1)^j B^j = 1 - dB + \frac{d(d-1)}{2} B^2,$$

and thus, if d is non-integer, x_t will depend on all its past history, and higher the value of d is, the higher the dependence between the observations is. Thus, the parameter d can be taken as a measure of the degree of dependence in the data. An I(d) process with positive d implies that its spectral density function, (f(λ)), which is the Fourier transform of the autocovariances, tends to infinite at the zero frequency, i.e.,

$$f(\lambda) \quad \rightarrow \infty \quad as \quad \lambda \rightarrow 0.$$

[1] B is the backshift operator, i.e., $B^k x_t = x_{t-k}$.

This phenomenon is very common in aggregated time series data, and taking first differentiation, which is the usual approach, produces sometimes series which an estimated spectral density function with a value close to zero at the zero frequencies, i.e., f(0) = 0 which indicates overdifferentiation. This observation, noticed among others by Granger (1980) was the origin of fractional integration in time series where the differencing parameter d can be a fractional value constrained between 0 and 1.

We estimate d by using the Whittle function as expressed in the frequency domain (Dahlhaus, 1989) and use a version of a Lagrange Multipliker (LM) test developed in Robinson (1994) that is very appropriate even in nonstationary contexts.[2] The functional form of this methodology can be found in any of the numerous empirical applications of his tests (see, e.g., Robinson and Gil-Alana, 1997; Gil-Alana and Moreno, 2012; etc.)

3. The dataset

Until recently, there has been a lack of geopolitical risk indicators considered able to effectively and simultaneously measure the perception of several sections of the society. For instance, the indices constructed by the international Country Risk Guide (ICRG) are mostly subjective, as they are premised on the insights of certain analysts following developments in a specific region or country (Caldara and Iacoviello, 2018). However, Caldara and Iacoviello (2018) have introduced a geopolitical risk indicator that is not only consistent over time, but also computes geopolitical risk as viewed by the public, the press, policy-makers and international global investors in real time. In this study, we have used the datasets provided by Caldara and Iacoviello (2018), which have been generated through textual analysis. Textual analysis is based on searching in major domestic as well

[2] Robinson's (1994) method is valid for any real d and thus, it is not constrained to the stationary range (i.e., $d < 0.5$).

as global newspapers for each country. Caldara and Iacoviello (2018) calculated the index for each country by tallying the frequency of articles associated with geopolitical risk in each newspaper on a monthly basis. Thereafter, the index is normalized to average a figure of 100 in the 2000-2009 period.

The search captures newspapers articles that have six sets of words including: Group 1 which has words that are associated with unambiguous reference to geopolitical risk in addition to reference to military-connected tensions that involve important regions of the world as well as the country under investigation. Group 2 involves words that are directly associated with nuclear crises. Groups 3 and 4 involve reference words that are associated with threats of wars as well as threats of terrorism, respectively. Lastly, Groups 5 and 6 focus on press coverage of actual and harmful geopolitical events, which have the potential to generate further geopolitical uncertainty including acts of terrorism or the commencement of a war.

The description of the searched words is contained in Table 1. There are six categories of words and the first four clusters are connected to geopolitical tensions and threats, while the remaining two clusters are connected to geopolitical acts and events. The datasets used in this study is for 19 countries: Saudi Arabia, Argentina, Brazil, China, Colombia, Hong Kong, India, Indonesia, Israel, Korea, Malaysia, Mexico, Philippines, Russia, South Africa, Thailand, Turkey, Ukraine and Venezuela, covering the time period from January 1985 to February 2020. The descriptive statistics of the series are reported in Table 2 and it is shown that with a mean of 126.25 points, Ukraine has the greatest geopolitical risk among all the countries. The country has been in conflict with its larger, north-eastern neighbour -Russia in recent times. Other countries with high geopolitical risks and currently in tension or conflict their neighbours include Russia and South Korea.

Table 1: Description of searched words

Search category	Words
1. Geopolitical Threats	Geopolitical AND (risk* OR concern* OR tension* OR uncertainty*) "United States" AND tensions AND (military OR war OR geopolitical OR coup OR guerrilla OR warfare) AND ("Latin America" OR "Central America" OR "South America" OR Europe OR Africa OR "Middle East" OR "Far East" OR Asia).
2. Nuclear Threats	("nuclear war" OR "atomic war" OR "nuclear con "nuclear missile*") AND (fear* OR threat* OR risk* OR peril* OR menace*)
3. War Threats	"war risk*" OR "risk* of war" OR "fear of war" OR "war fear*" OR "military threat*" OR "war threat*" OR "threat of war" ("military action" OR "military operation" OR "military force") AND (risk* OR threat*).
4. Terrorist Threats	"terrorist threat" OR "terrorist threats" OR "menace of terrorism" OR "terrorism menace" OR "threat of terrorism" OR "terrorist risk" OR "terror risk" OR "risk of terrorism" OR "terror threat" OR "terror threats".
5. War Acts	(beginning OR outbreak OR onset OR escalation OR start) "of the war" (war OR military) AND ("air strike" OR "heavy casualties").
6. Terrorist Acts	"terrorist act" OR "terrorist acts"

Source: Caldara and Iacoviello (2018).

Table 2: Descriptive statistics

Country	**Max.**	**Min.**	**Mean**	**Std. Dev.**
ARGENTINA	371.01	33.63	111.94	43.76
BRAZIL	221.41	43.02	103.22	29.26
CHINA	251.50	56.53	105.25	29.67
COLOMBIA	171.85	22.78	80.39	28.38
HONG KONG	373.78	41.06	100.44	40.53
INDIA	246.56	48.59	93.61	28.06
INDONESIA	275.94	20.20	74.64	31.96
ISRAEL	179.20	45.78	84.71	22.77
KOREA	274.42	38.70	108.74	38.87

MALAYSIA	278.88	17.49	90.51	35.16
MEXICO	214.01	55.03	98.56	25.40
PHILIPPINES	215.54	35.25	99.33	35.21
RUSSIA	241.38	47.68	105.57	28.93
SAUDI ARABIA	210.64	33.18	93.08	33.42
SOUTH AFRICA	301.71	13.83	111.85	46.55
THAILAND	296.19	35.44	94.70	38.92
TURKEY	320.26	32.63	111.62	43.56
UKRAINE	382.87	22.18	126.25	63.56
VENEZUELA	233.48	16.38	86.14	38.86

4. Empirical results

We work with both the original and the deseasonalized data. In all cases we examine the following model,

$$y_t = \beta_0 + \beta_1 t + x_t; \qquad (1 - L)^d x_t = u_t, \qquad t = 0, 1, ..., \qquad (1)$$

where y_t is the series under investigation, β_0 and β_1 are unknown coefficients referring respectively to an intercept and a linear time trend, and x_t is I(d) so that u_t is I(0) expressed in terms of a white noise or as a weakly autocorrelated process.

Tables 3 reports the results for the original data with white noise errors. Tables 4 also deals with white noise errors but we use the deseasonalized data. Tables 5 and 6 refer respectively to the original and deseasonalized data with autocorrelated errors.

We first conducted the estimation of d for the three standard cases of i) no terms, ii) with an intercept, and iii) with an intercept and a linear time trend, testing the significance of its coefficients by means of the t-values of the estimated parameters. We report across Tables 3 – 6, only the most appropriate specification for each series according to these deterministic terms.

Starting with Table 3 (original data with white noise error) we first notice that the time trend is statistically significant in 8 out of the 19 series examined, namely, in Saudi Arabia, Argentina, China, Hong Kong, Mexico, South Africa, Turkey and Venezuela, with the coefficient being positive in all cases except for Argentina and South Africa which present a negative value. The estimates of d are in the range (0, 1) in all cases, implying long memory behaviour; however, we observe some differences across the countries, the values ranging between 0.26 (Malaysia) and 0.49 (Ukraine). For twelve of the series, the values are significantly below 0.5, implying covariance or second order stationary (i.e., Malaysia, 0.26; South Africa and Mexico, 0.29; Argentina and Brazil, 0.34; Venezuela, 0.35; Colombia and Indonesia, 0.37; Korea, Philippines and Thailand, 0.38; and Russia, 0.41). For the remaining seven countries, the confidence intervals include both stationary and nonstationary values.

Table 3: Estimated coefficients in the model with white noise errors (original data)

Country	No terms	An intercept	A linear time trend
ARGENTINA	0.34 (0.26, 0.44)	4.9817 (39.82)	-0.0014 (-2.79)
BRAZIL	0.34 (0.28, 0.41)	4.6632 (65.15)	---
CHINA	0.52 (0.46, 0.59)	4.3552 (37.96)	0.0011 (1.84)
COLOMBIA	0.37 (0.32, 0.42)	4.2776 (41.83)	---
HONG KONG	0.47 (0.41, 0.54)	4.2321 (28.35)	0.0013 (1.92)
INDIA	0.44 (0.38, 0.51)	4.4689 (49.06)	---
INDONESIA	0.37 (0.33, 0.42)	4.1357 (39.86)	---
ISRAEL	0.43 (0.37, 0.50)	4.3389 (39.86)	---
KOREA	0.38 (0.31, 0.47)	4.5639 (39.86)	---
MALAYSIA	0.26 (0.20, 0.32)	4.3795 (39.86)	---
MEXICO	0.29 (0.22, 0.37)	4.3179 (39.86)	0.0012 (5.28)
PHILIPPINES	0.38 (0.33, 0.44)	4.5542 (39.86)	---
RUSSIA	0.41 (0.36, 0.48)	4.5917 (39.86)	---
SAUDI ARABIA	0.43 (0.37, 0.51)	4.1054 (28.82)	0.0012 (1.98)
SOUTH AFRICA	0.29 (0.23, 0.37)	5.1517 (39.86)	-0.0025 (-7.03)
THAILAND	0.38 (0.31, 0.46)	4.4935 (39.86)	--

TURKEY	0.45 (0.38, 0.53)	4.3473 (27.60)	0.0013 (1.75)
UKRAINE	0.49 (0.44, 0.55)	4.6498 (25.26)	---
VENEZUELA	0.35 (0.29, 0.42)	3.9570 (28.31)	0.0020 (3.47)

In parenthesis in the third and fourth columns, the corresponding t-values.

Table 4: Estimated coefficients in the model with white noise errors (deseasonalized data)

Country	No terms	An intercept	A linear time trend
ARGENTINA	0.33 (0.27, 0.41)	4.9984 (48.47)	-0.0014 (-3.34)
BRAZIL	0.35 (0.30, 0.41)	4.6776 (69.22)	---
CHINA	0.54 (0.48, 0.61)	4.3838 (39.98)	0.0011 (1.75)
COLOMBIA	0.39 (0.34, 0.44)	4.2643 (43.08)	---
HONG KONG	0.50 (0.45, 0.57)	4.2683 (29.01)	0.0013 (1.77)
INDIA	0.48 (0.42, 0.54)	4.4897 (49.99)	---
INDONESIA	0.39 (0.35, 0.44)	4.1387 (38.96)	---
ISRAEL	0.45 (0.40, 0.52)	4.2920 (50.45)	---
KOREA	0.40 (0.33, 0.48)	4.6078 (44.53)	---
MALAYSIA	0.29 (0.24, 0.36)	4.4020 (64.17)	---
MEXICO	0.30 (0.24, 0.38)	4.3231 (79.60)	0.0012 (5.65)
PHILIPPINES	0.40 (0.36, 0.46)	4.5304 (46.84)	---
RUSSIA	0.33 (0.38, 0.49)	4.5916 (55.11)	---
SAUDI ARABIA	0.44 (0.39, 0.51)	4.1427 (31.04)	0.0011 (1.93)
SOUTH AFRICA	0.32 (0.26, 0.40)	4.1335 (55.29)	-0.0024 (-6.47)
THAILAND	0.39 (0.33, 0.47)	4.5169 (40.65)	---
TURKEY	0.47 (0.41, 0.54)	4.3784 (29.55)	0.0012 (1.70)
UKRAINE	0.50 (0.45, 0.56)	4.7241 (27.36)	---
VENEZUELA	0.35 (0.30, 0.42)	3.9708 (30.90)	0.0019 (3.73)

In parenthesis in the third and fourth columns, the corresponding t-values.

Table 4 focuses on the deseasonalized data, the results being fairly similar. Thus, evidence of time trends is obtained in exactly the same countries as in Table 3, once more, observing negative trends in the cases of Argentina and South Africa. If we look now at the estimated differencing parameters, we observe that the values are slightly smaller than in the previous case, though similarly to that case, stationarity takes places exactly in the same countries, the values ranging now between 0.29 (Malaysia) and 0.54 (China). Nevertheless, the fact that all values are significantly below 1 implies mean reversion with shocks disappearing by themselves in the long run.

We next allow for autocorrelated disturbances. Tables 5 and 6 reproduce Tables 3 and 4 though allowing for weak autocorrelation throughout the exponential model of Bloomfield (1973)[3]. Starting with the original data (Table 5), the time trend is required in the same cases as with white noise errors except for Hong Kong and Venezuela where the time trend is now insignificant; the estimated differencing parameter ranges once more in all cases within the interval (0, 1) implying long memory and fractional integration. These values are now between 0.20 (Argentina) and 0.62 (Ukraine), and for this latter country the confidence band contains values which are all strictly higher than 0.5, implying nonstationary behaviour. As in previous cases, negative trends are observed for Argentina and South Africa.

Looking at the deseasonalized data (Table 6) the time trend is now statistically significant only for Argentina and South Africa (with a negative coefficient) and for Mexico and Venezuela (with a positive time trend), and the values of d are similar to the previous case, with the values of d ranging between 0.31 (Thailand) and 0.67 (Ukraine).

Table 7 summarizes the results in terms of the estimated values of d. We have marked in bold the cases where stationarity ($d < 0.5$) was detected. We see a higher proportion within the original data. Nevertheless, for Argentina, Mexico and Thailand, stationarity is detected in the four cases examined. On the other extreme, for China, Hong Kong, India, Israel, Turkey and Ukraine, there is no evidence of stationarity in any of the four cases presented, and for Ukraine, nonstationarity ($d > 0.50$) is observed under the assumption of autocorrelated errors.

[3] This is a non-parametric approach that approximates autoregressions in I(0) contexts.

Table 5: Estimated coefficients in the model with autocorrelated errors (original data)

Country	No terms	An intercept	A linear time trend
ARGENTINA	0.20 (0.09, 0.34)	4.9591 (68.60)	-0.0014 (-4.90)
BRAZIL	0.34 (0.25, 0.44)	4.6672 (62.21)	---
CHINA	0.52 (0.43, 0.64)	4.3552 (37.96)	0.0011 (1.84)
COLOMBIA	0.48 (0.39, 0.58)	4.2724 (27.93)	---
HONG KONG	0.60 (0.44, 0.74)	4.2344 (22.14)	---
INDIA	0.46 (0.36, 0.57)	4.4643 (47.16)	---
INDONESIA	0.53 (0.46, 0.62)	4.0420 (21.79)	---
ISRAEL	0.43 (0.34, 0.54)	4.3389 (50.88)	---
KOREA	0.34 (0.21, 0.50)	4.5924 (53.48)	---
MALAYSIA	0.30 (0.23, 0.40)	4.3498 (49.21)	---
MEXICO	0.25 (0.15, 0.38)	4.3142 (86.13)	0.0012 (6.25)
PHILIPPINES	0.44 (0.37, 0.54)	4.5517 (36.31)	---
RUSSIA	0.46 (0.36, 0.56)	4.5829 (45.92)	---
SAUDI ARABIA	0.46 (0.36, 0.60)	4.0858 (26.40)	0.0013 (1.76)
SOUTH AFRICA	0.35 (0.36, 0.49)	5.1361 (46.28)	-0.0025 (-5.46)
THAILAND	0.28 (0.20, 0.38)	4.4803 (58.44)	---
TURKEY	0.40 (0.31, 0.55)	4.3580 (32.04)	0.0012 (2.14)
UKRAINE	0.62 (0.53, 0.74)	4.6022 (18.37)	---
VENEZUELA	0.35 (0.26, 0.45)	3.9570 (28.31)	0.0020 (3.47)

In parenthesis in the third and fourth columns, the corresponding t-values.

Table 6: Estimated coefficients in the model with autocorrelated errors (deseasonalized data)

Country	No terms	An intercept	A linear time trend
ARGENTINA	0.33 (0.24, 0.47)	4.9984 (48.47)	-0.0014 (-3.34)
BRAZIL	0.41 (0.33, 0.52)	4.7149 (51.37)	---
CHINA	0.55 (0.45, 0.68)	4.4429 (40.97)	---
COLOMBIA	0.52 (0.45, 0.63)	4.2252 (25.46)	---
HONG KONG	0.64 (0.48, 0.79)	4.3013 (23.27)	---
INDIA	0.52 (0.41, 0.65)	4.4758 (43.62)	---
INDONESIA	0.53 (0.46, 0.62)	4.0097 (23.29)	---

ISRAEL	0.47 (0.38, 0.59)	4.2719 (45.06)	---
KOREA	0.42 (0.30, 0.60)	4.6010 (40.87)	---
MALAYSIA	0.39 (0.29, 0.50)	4.3607 (39.71)	---
MEXICO	0.32 (0.22, 0.45)	4.3286 (53.07)	0.0012 (3.43)
PHILIPPINES	0.50 (0.42, 0.60)	4.4790 (31.95)	---
RUSSIA	0.50 (0.42, 0.63)	4.5794 (40.20)	---
SAUDI ARABIA	0.52 (0.43, 0.66)	4.1833 (26.98)	---
SOUTH AFRICA	0.38 (0.26, 0.56)	5.1043 (44.71)	-0.0024 (-4.95)
THAILAND	0.31 (0.23, 0.41)	4.4937 (58.46)	---
TURKEY	0.51 (0.40, 0.62)	4.4879 (31.72)	---
UKRAINE	0.67 (0.59, 0.80)	4.7609 (19.10)	---
VENEZUELA	0.41 (0.33, 0.50)	3.9934 (25.62)	0.0019 (2.82)

In parenthesis in the third and fourth columns, the corresponding t-values.

Table 7: Summary table on persistence

Country	Original data		Deseasonalized data	
	White noise	Autocorrelation	White noise	Autocorrelation
ARGENTINA	**0.34 (0.26, 0.44)**	**0.33 (0.27, 0.41)**	**0.20 (0.09, 0.34)**	**0.33 (0.24, 0.47)**
BRAZIL	**0.34 (0.28, 0.41)**	**0.35 (0.30, 0.41)**	**0.34 (0.25, 0.44)**	0.41 (0.33, 0.52)
CHINA	0.52 (0.46, 0.59)	0.54 (0.48, 0.61)	0.52 (0.43, 0.64)	0.55 (0.45, 0.68)
COLOMBIA	**0.37 (0.32, 0.42)**	**0.39 (0.34, 0.44)**	0.48 (0.39, 0.58)	0.52 (0.45, 0.63)
HONG KONG	0.47 (0.41, 0.54)	0.50 (0.45, 0.57)	0.60 (0.44, 0.74)	0.64 (0.48, 0.79)
INDIA	0.44 (0.38, 0.51)	0.48 (0.42, 0.54)	0.46 (0.36, 0.57)	0.52 (0.41, 0.65)
INDONESIA	**0.37 (0.33, 0.42)**	**0.39 (0.35, 0.44)**	0.53 (0.46, 0.62)	0.53 (0.46, 0.62)
ISRAEL	0.43 (0.37, 0.50)	0.45 (0.40, 0.52)	0.43 (0.34, 0.54)	0.47 (0.38, 0.59)
KOREA	**0.38 (0.31, 0.47)**	**0.40 (0.33, 0.48)**	0.34 (0.21, 0.50)	0.42 (0.30, 0.60)
MALAYSIA	**0.26 (0.20, 0.32)**	**0.29 (0.24, 0.36)**	**0.30 (0.23, 0.40)**	0.39 (0.29, 0.50)
MEXICO	**0.29 (0.22, 0.37)**	**0.30 (0.24, 0.38)**	**0.25 (0.15, 0.38)**	**0.32 (0.22, 0.45)**
PHILIPPINES	**0.38 (0.33, 0.44)**	**0.40 (0.36, 0.46)**	0.44 (0.37, 0.54)	0.50 (0.42, 0.60)
RUSSIA	**0.41 (0.36, 0.48)**	**0.33 (0.38, 0.49)**	0.46 (0.36, 0.56)	0.50 (0.42, 0.63)
SAUDI ARABIA	0.43 (0.37, 0.51)	0.44 (0.39, 0.51)	0.46 (0.36, 0.60)	0.52 (0.43, 0.66)
SOUTH AFRICA	**0.29 (0.23, 0.37)**	**0.32 (0.26, 0.40)**	**0.35 (0.36, 0.49)**	0.38 (0.26, 0.56)
THAILAND	**0.38 (0.31, 0.46)**	**0.39 (0.33, 0.47)**	**0.28 (0.20, 0.38)**	**0.31 (0.23, 0.41)**
TURKEY	0.45 (0.38, 0.53)	0.47 (0.41, 0.54)	0.40 (0.31, 0.55)	0.51 (0.40, 0.62)
UKRAINE	0.49 (0.44, 0.55)	0.50 (0.45, 0.56)	0.62 (0.53, 0.74)	0.67 (0.59, 0.80)

VENEZUELA	**0.35 (0.29, 0.42)**	**0.35 (0.30, 0.42)**	**0.35 (0.26, 0.45)**	0.41 (0.33, 0.50)

In bold, evidence of stationarity.

5. Conclusions

In this article we have examined geopolitical risk from a time series viewpoint. We examine 19 countries covering the time period from January 1985 to February 2020. The countries examined were Saudi Arabia, Argentina, Brazil, China, Colombia, Hong Kong, India, Indonesia, Israel, Korea, Malaysia, Mexico, Philippines, Russia, South Africa, Thailand, Turkey, Ukraine and Venezuela, and the methodology used was based on fractional integration. We use both seasonal and deseasonalized data and the results can be summarized as follows: evidence of time trends are only observed in some of the countries examined, and this evidence is consistent across the different modelling assumptions in the case of positive trends for Mexico and Venezuela, and negative ones for Argentina and South Africa. If we focus on the degree of integration, all values of the differencing parameter are within the range (0, 1) supporting fractional integration and long memory, though we observe some heterogeneity across countries. Thus, evidence of stationarity (i.e., values of d significantly below 0.5) is found in the cases of Argentina, Brazil, Malaysia, Mexico, South Africa, Thailand and Venezuela, for the two types of data examined (seasonal and deseasonalized), but also for Colombia, Indonesia, Korea, Philippines and Russia with the original (seasonal) data only. For the remaining countries (i.e., South Africa, China, Hong Kong, India, Israel, Turkey and Ukraine) nonstationarity is found in all cases, implying that though mean reversion is achieved ($d < 1$) shocks in these countries will have longer lasting effects. Therefore, there is a need for the governments of these countries (especially the ones with high geopolitical risks such as Ukraine and Turkey) to introduce and implement steps that will attenuate their geopolitical risks. These strategies include the involvement in diplomatic contact with other countries that they may be in conflict or undergoing tense relations with or are likely to in the near future (or an enhancement of such contacts if they already exist). Moreover, instruments of restraint, such as arms control and confidence and security-building measures (CSBMs) should be encouraged.

This article provides a line of research that can be extended in several directions. For instance, the use of non-linear structures, either in the deterministic part of the model or even in the stochastic part can be developed in the analysis of these data. Note that fractional integration and nonlinear structures are very much related and thus, it worths its study. In addition, since the main goal in the paper is the issue of persistence in the data, other semiparametric methods of fractional integration can be employed as a robustness approach of the results reported. Work in these directions is now in progress.

Data statement

The data that support the findings of this study are available from the corresponding author upon reasonable request.

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